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ENSEMBLE KALMAN FILTERING FOR ASSIMILATION OF GPS-BASED IONOSPHERIC OBSERVATIONS

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Summary: In this paper we present our recent research development in the area of ionospheric specification using GPS-based observations. NOAA's TEC specification methodology (Gauss-Markov Kalman filter) over the continental United States has lately been expanded to the multi-regional domains and to the entire globe. Furthermore, the potential of ensemble Kalman filter to assimilate GPS-based observations to a coupled thermosphere and ionosphere general circulation model is being examined.

1 INTRODUCTION

The NOAA-Space Weather Prediction Center (SWPC) is the designated official source for the United State's space weather prediction, forecast and warning services. One of SWPC's operational products is the United States Total Electron Content (US-TEC). On a near real-time basis US-TEC reconstructs the three-dimensional distribution of electron density with Gauss-Markov Kalman filtering of ground-based GPS observations using International Reference Ionosphere 2001 as a background model, and computes TEC over the continental United States (CONUS)1,2. Its target users are the positioning and navigation community, and for instance, SWPC is developing an ionospheric correction product for the U.S. National Geodetic Survey's Online Positioning User Service based on the US-TEC output3. This regional product has been shown to have an average RMSE in the slant path TEC of 2.4 TEC units, equivalent to less than 40 cm of signal delay at L1 frequencies4. This result is consistent with the results from an absolute validation method, which indicates an uncertainty in the maps of 2.7 TEC units, a little over 40 cm of signal delay at L1[5].

Recently, the domain of Gauss-Markov Kalman filtering has been expanded from CONUS to multi-regional domains and then to a global domain (see Figure 1). There is an on-going effort to assimilate space-based GPS observations to improve the electron density specification over oceans. We furthermore attempt to improve our ability to reconstruct the ionospheric electron density from GPS-based observations by taking advantage of the tightly coupled nature of ionosphere and thermosphere as represented in general circulation models of the thermosphere-ionosphere system

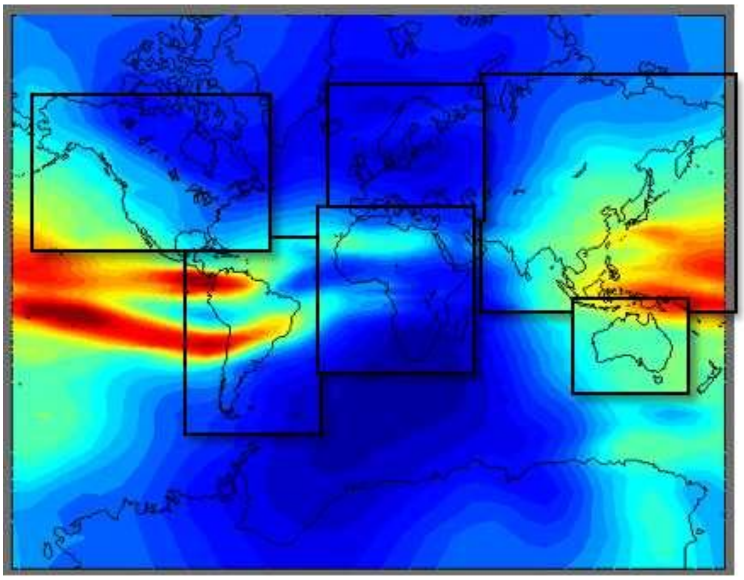

Figure 1: The reconstructed TEC from the ground-based GPS observations over the globe using the Gauss-Markov Kalman filter implemented in operational US-TEC. The 6 continental areas annotated by black boxes are the regional domains.

2 ENSEMBLE KALMAN FILTERING: POTENTIAL AND CHALLENGES

The ensemble Kalman Filter (EnKF) is a Monte-Carlo approximation of a sequential Bayesian filtering process. Ensemble (Monte-Carlo) samples are used to estimate the covariance of the prior distribution of the model state and of observations. The algorithm consists of recursive application of an analysis (update) step in which the prior ensemble estimate of the state is updated by observations to produce a posterior (analysis), and a forecast step in which the posterior sample is propagated forward in time with a dynamical model to the next observation time. There is no need to compute explicitly the enormous prior covariance matrices that are associated with large dynamical models. The EnKF has been shown to work well with both nonlinear model dynamics and nonlinear relationships between observations and model state variables[6], and there is no need to linearize a forecast model or a forward (observation) operator. The resulting ease of implementation has led to a number of atmospheric assimilation applications by groups that may not have the resources to develop variational systems like those used for operational numerical weather prediction. Important recent developments in EnKF are related to sampling error issues, often encountered in Monte-Carlo based methods with a small sample number compared to the degrees of freedom in the dynamical model. To attenuate spurious sample correlations, the impact of observations is localized. To avoid filter divergence (in which ensemble samples diverge gradually from the truth or the observation) due to insufficient variance in the sample posterior/forecast covariance the sample forecast covariance is artificially inflated.

In this paper we examine the potential of EnKF to assimilate GPS-based observations to a coupled thermosphere and ionosphere general circulation model. An EnKF assimilation system has been constructed using the National Center for Atmospheric Research Data Assimilation Research Testbed[7]. We are interested in not only reconstructing the three-dimensional distribution of electron density, but also inferring thermospheric paramters. This approach complements the approach taken by other ionospheric data assimilation projects in which thermospheric states such as neutral winds are considered to be external drivers. Here, the thermospheric feedback are taken into account in both forecast and analysis steps through coupled dynamics of the thermospheric states (i.e., temperature, winds, and major compositions) ionospheric state (i.e., electron density) captured in the model. Some of EnKF challenges specific to the ionosphere and thermosphere application arises from a heterogeneous irregular observational network of GPS stations and from model error issues regarding model error growth and also systematic bias. We discuss how these challenges can be rectified advanced ensemble techniques such as adaptive covariance inflation and localization of covariance.

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